ERPs and Visual Signal Detection Performance: Classification Functions Based on Wavelet Decompositions

Leonard J. Trejo
University of Illinois at Urbana-Champaign

Michelle M. Mullane
United States International University

Introduction

- The wavelet transform is an important new signal processing tool that is revolutionizing the analysis of signals such as the ERP and the EEG. Its most salient aspect is the replacement of frequency by scaling either in time (one-dimensional) or in space (two-dimensional). These correspond, respectively, to time-series analysis and to image processing. As a result, the bandwidth is proportional to frequency.
- This feature, which is common to most real broadband signals, makes wavelets particularly suitable for the analysis of transients or brief changes in the signal. This also contrasts with the Fourier transform, which has a fixed bandwidth at all frequencies.
- The purpose of this research was to determine the extent to which wavelet transforms of ERPs discriminate between high- and low signal detection and classification performance over periods of about 30 s.

Methods

- **Subjects**

  Eight experienced male technicians with occupational experience in monitoring electronic displays (ages 18 to 43y). All subjects had normal or corrected vision.

- **Task**

  The task was presented on a radar-like display (Figure 1). Subjects pressed "T" or "NT" buttons to detect targets and nontargets, and rated their confidence in each detection response on a 3-point scale using a mouse. Task-relevant stimuli were triangles, with or without central dots, presented for 50 ms at three signal-to-noise ratios. The intertrial interval varied between 2.5 and 3.0 s. Each subject was trained to a stable level of performance on the task.

- **Testing procedure**

  The task was performed in two sessions spaced one week apart. In each session, about 10 blocks of 50-72 trials each were performed. The first block was a baseline run, in which ERPs were recorded but no responses were allowed. Subsequent blocks contained stimuli of varying S/N ratios. Mapping between stimuli and responses changed with each new block to enforce controlled processing.

- **ERP recording**

  ERPs were recorded from electrodes Fz, Cz, and Pz, referred to averaged mastoids. EOGs were also recorded and artifacts were corrected off line. Visual fixation was monitored and controlled with an infrared eye tracker.

Results

- Sample average ERP data for five subjects appear in Figures 2-4. Averages were computed separately for high- and low performance (median split) blocks of trials. Performance was defined as a linear composite of speed, accuracy, and confidence measures using the formula described by Trejo, Kramer, & Arnold (1995):

$$PF_1 = .33\ accuracy + .53\ confidence - .51\ reaction\ time.$$

- The ERP averages of 7 to 10 consecutive artifact-free ERPs were created using running means and a corresponding series of the running mean for the PF1 measure. Both series were median-split to form low- and high-PF1 samples. We computed the discrete wavelet transform for each of the block-averaged ERPs using the Daubechies D4 wavelet (Daubechies, 1992). The high/low average DWTs for one subject appear in Figures 5-7.

- The ERP block averages also served as the input matrix for a covariance-based, mean-centered PCA. For each subject, six factors were retained and rotated using the varimax method. Factor scores were computed for each sample (low- and high PF1). Figure 8 shows an example of the factor loadings for one subject (S2). The best three factors were retained and combined for classifications.
- Classification method. Block averages of n=1, 2, 4, ..., 64 blocks were created by drawing 1000 random sub-samples of size n from each of the samples. Each block average was classified by its multivariate Euclidean distance from the mean vector for the high or low PF1 samples (Figures 9 & 10).
- A Kruskal-Wallis rank sum test was used to test the difference in the number of blocks averaged required to correctly classify a block average with 70% or 90% accuracy. For both accuracy levels, the DWT required significantly fewer blocks than the PCA (70%: c2(1)=8.98, p=.003; 90%: c2(1)=9.78, p=.002, Figure 11).

Conclusions

1. As compared to PCA scores, the DWT transform of short-term ERP averages provided for better classification of performance states in a signal detection and classification task. In eight of eight subjects, the DWT classification functions exceeded the PCA functions at all averaging levels. At the two levels tested, 70% and 90%, the DWT required fewer trials to correctly classify ERP averages than the PCA.
2. The average number of blocks required to correctly classify 70% of the averages was 1.6 for the DWT. This corresponds to a time on task of 48 seconds. Thus a DWT-based algorithm may provide for on-line ERP-based assessment of human performance. Such measurements could provide for analysis of dynamic changes in task performance in experimental or applied settings.